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Forecasting the Exchange Rate between AUD and USD with HAR model

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ABSTRACT

The exchange rate is essential to global financial markets. Based on the approximate long memory Heterogeneous Autoregressive (HAR) model proposed by Corsi, we estimate the volatility using 5-minute high-frequency data on the US dollar exchange rate against the Australian dollar from January 15, 2019, to September 16, 2021. The HAR-RV model performs well in describing volatility and forecasting accuracy. The empirical results indicate that daily, weekly, and monthly volatility positively influences exchange rate volatility, especially in the mid-term and the long-term. This paper provides a forecasting method to predict exchange rate volatility

***Keywords**: Volatility Forecasting; Exchange Rate; Realized Volatility; HAR Model; High-Frequency Data.*

1. INTRODUCTION

The exchange rate is the ratio of one country's currency to another country's currency. It is the price of one currency expressed in another currency. Nowadays, the exchange rate plays an important role. The impact of exchange rate changes on the economy is mainly reflected in prices and indirectly affects the domestic stock market through prices and national income. The decline in the exchange rate of local currency stimulates exports, weakens the purchasing power of imported products, increases national income, increases the price level, and induces surplus funds to flow into the stock market; vice versa. The exchange rate is not only the concentrated embodiment of a country's economic quality but also the embodiment of a country's comprehensive national strength, including a country's political and military influence on a global scale. The exchange rate is also a kind of power - it determines how much wealth a country obtains globally. A country can also use its exchange rate to export inflation or deflation.

Volatility measures the uncertainty of asset return. It represents the risk of financial assets and has become a very important feature of financial assets. It is widely used in portfolio analysis, risk management, and option pricing. At the same time, volatility can not be observed directly. Therefore, volatility modeling has become one of the research hotspots in the global financial field.

For a long time, scholars in various countries have not only done in-depth research on volatility and its model in theory but also estimated and measured volatility with empirical methods. Generally speaking, the methods to measure volatility can be divided into the parametric method and the nonparametric method. The parameter method, as the name suggests, refers to the use of a certain parameter model to measure volatility. Among them, the ARCH model of Engle [1] and the GARCH model proposed by Bollerslev [2] are widely used, which is mainly due to the fact that such models can well describe the phenomena of volatility aggregation and sharp peak and thick tail of return. The nonparametric method refers to the direct calculation of daily transaction data according to a certain method. Taking the realized volatility based on high-frequency data proposed by Andersen et al. [3, 4] as an example, it can not only accurately describe the volatility but also is not limited by the model.

Most of these realized measures derived from high-frequency data are based on realized volatility, and the most essential model in the research on realized volatility is the heterogeneous autoregressive model proposed by Corsi [5, 6] on the basis of heterogeneous market hypothesis, that is, the heterogeneous autoregressive model of the realized volatility model, referred to as HAR-RV model for short. The core idea of the HAR-RV model is to use the daily, weekly, and monthly fluctuation components to simulate the trading behavior of different types of market traders. Through the analysis of empirical data, it is found that the model can well describe the long memory characteristics of realized volatility and explain the reasons for these relevant characteristics of realized volatility. Most importantly, compared with the ARFIMA model, which is widely used in describing long memory characteristics, the estimation of the HAR-RV model is much simpler.

This paper uses the HAR-RV model for volatility forecasting the exchange rate between AUD and USD. We consider the short term, medium-term and long term (daily, weekly and monthly) volatility to research the exchange market in order to find out the relationship between daily, weekly and monthly volatility and lag one exchange rate volatility. The results of the in-sample analysis suggest that historical trading volume positively affects the volatility of the exchange rate between AUD and USD. At the same time, we find that historical trading volume and exchange rate volatility between AUD and USD contain some forecasting information. However, the accuracy will be reduced when more factors are considered in the model.

This paper is organized as follows. Section 2 describes the samples and data, including daily, weekly, and monthly data. Section 3 introduces the methodology, the HAR-RV model, its advantages and disadvantages, and the current application of the model. The fourth section makes an empirical test on the in-sample analysis. Section 5 gives the conclusions.

2. DATA

The sample consists of 5-minute-frequency trading data of the exchange rate of USD to AUD. The sample period starts from January 15, 2019, and ends on September 16, 2021. And the source of the data is Yahoo Finance. We use the data to calculate the daily, weekly, and monthly RV.

Fig. 1 shows the relationship between the daily RV and the date. The daily volatility remained stable from January 15, 2019, to September 1, 2019, then increased sharply to about six on September 2, 2019. On September 3, 2019, the daily volatility dropped to about 0 and remained stable for about 11 months. After that, the volatility rose rapidly to the highest in August 2020, about 21. And then declined sharply to about 1 in September 2020 and remained stable to the end.

Fig.2 presents the relationship between weekly RV and the date over the sample period. The weekly RV increased to 1.8 in September 2019 and remained stable until September 2019. Then, the volatility declined to about 0.1 from September 2019 to July 2020. In July 2020, the weekly RV reached the highest level, about 9.5. After that, the weekly RV decreased to about 0.1 until the end of the sample period.

From Fig. 3, we can see that the monthly RV increased from 0.2 to 0.7 during September 2019. Then dropped to 0.2 and remained stable until July 2020. The monthly RV rose to 4.9, the highest level in August 2020. After that, the volatility decreased sharply to about 0.5 from August 2020 to October 2020.

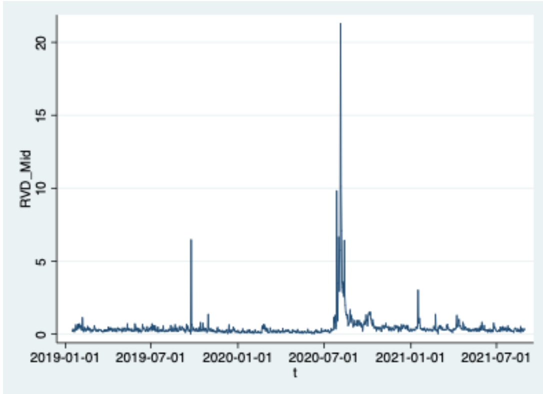

Figure. 1. Daily volatility dynamics of the exchange rate between AUD and USD.

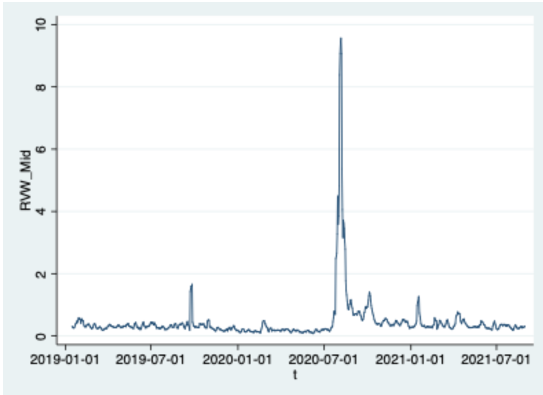

Figure. 2. Weekly volatility dynamics of the exchange rate between AUD and USD.

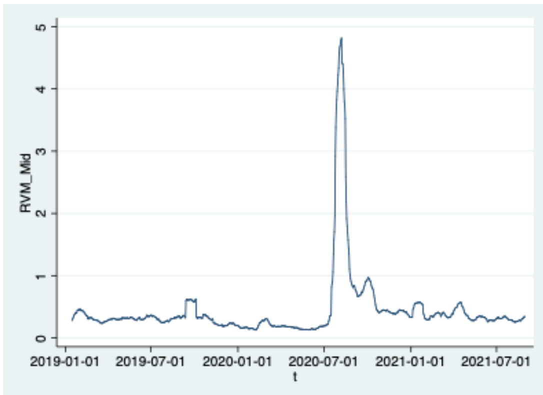

Figure.3. Monthly volatility dynamics of the exchange rate between AUD and USD.

3. METHOD

In this section, to predict the volatility of the exchange rate between USD and AUD, we introduce the HAR-RV model.

Derived from the Heterogeneous Market Hypothesis and HARCH model proposed by Muller et al. [7, 8], Corsi [5] proposed an approximate long-memory model for realized volatility called HAR, that is, Heterogeneous Autoregressive Realized Volatility model. According to this model, Corsi believes that an important factor causing market heterogeneity is the existence of three market agents with different investment periods: short-term, medium-term, and long-term (daily, weekly and monthly) investment periods. The heterogeneity of realized volatility can be captured by aggregating daily, weekly and monthly volatility components in autoregressive structure through the HAR model.

Then, we introduce the HAR-RV model, which contains the linear form and logarithmic form to determine whether the RV consists of a lot of information. We divide the trading day into M segments according to the method for calculating the RV presented by Andersen and Bollerslev [3]. The RV of the trading day t is denoted as RV_t^d, which can be expressed as

$$RV_t^d = \sum_{i=1}^{m} r_{t,i}^2 \quad (1)$$

where $r_{t,i}$, indicates the logarithmic rate of exchange for the i_{th} period of the trading day t.

Therefore, the weekly RV and the monthly RV of the trading day t, denoted as RV_t^w and RV_t^m, respectively, are defined as follows.

$$RV_t^w = \frac{RV_t^d + RV_{t-1}^d + RV_{t-2}^d + \cdots + RV_{t-5}^d}{6} \quad (2)$$

$$RV_t^m = \frac{RV_t^d + RV_{t-1}^d + RV_{t-2}^d + \cdots + RV_{t-24}^d}{25} \quad (3)$$

Using the 5-minute high-frequency data on the exchange rate, we show that the HAR model produces superior in-sample fitting.

4. EMPIRICAL ANALYSIS

4.1 Summary statistics

According to the following descriptive statistical analysis (Table 1) of the main variables, the daily volatility of the exchange rate between the Australian dollar and the US dollar is between 0.019 and 21.286, with a wide and violent fluctuation range. With regard to the weekly volatility of the exchange rate, the range is much smaller than the daily volatility, about 9.5. As for the monthly volatility of the exchange rate, the range is relatively small, at approximately 4.7.

The means of daily, weekly, and monthly volatility are very close. However, the standard deviation of daily, weekly, and monthly volatility gradually decreases, at about 0.996, 0.789, and 0.616, respectively.

Table 1. Descriptive statistics of variables.

Variable	Mean	Std. Dev.	Min	Max
rvd_mid	0.44759	0.99600	0.01929	21.28642
rvw_mid	0.44765	0.78850	0.07839	9.56837
rvm_mid	0.44789	0.61617	0.13023	4.81639
prvd_mid	0.44758	0.99600	0.01929	21.28642
prvw_mid	0.44767	0.78850	0.07839	9.56837
prvm_mid	0.44795	0.61615	0.13023	4.81639

4.2 Parameter estimations

In this section, we use OLS method to estimate the parameters of HAR model. Table 2 shows the parameter estimation of HAR-RV when predicting the exchange rate fluctuation of Australian dollar and US dollar in three different time periods (daily, weekly and monthly).

The estimation results of the HAR-RV model show that, in daily volatility forecasting, the 1-week and 1-month volatility are both positive. However, the daily volatility is only significantly positive in the 1-week forecast. In the weekly volatility forecast, the 1-day volatility and 1-week volatility are positive. And the weekly volatility is both significantly positive in the two volatility. The 1-week and 1-month volatility are both positive about the monthly volatility forecasting. But the monthly volatility is only significantly positive in the 1-month forecast. The result shows that the short-term (daily), medium-term (weekly), and long-term (monthly) volatility of the exchange rate between USD and AUD contains a lot of prediction information about the RV. In a word, the US dollar exchange rate against the Australian dollar is heterogeneous.

Table 2. Parameter estimation results of HAR-RV-type models.

	HAR-RV		
	1-day	1-week	1-month
β_0	-0.00058	-0.01096	0.00126
	(-0.02)	(-1.35)	(0.5)
$lnRV_t^d$	-0.0793	0.05774	0.0073
	(-2.42)	(-5.20)	(2.15)
$lnRV_t^w$	1.12568	0.76249	-0.02551
	(-17.46)	(-35.23)	(-3.84)
$lnRV_t^m$	-0.04523	0.20421	1.01555
	(-0.66)	(-8.83)	(143.24)
Adj-R^2	0.6447	0.9348	0.9900

5. CONCLUSION

This paper mainly uses 5-minute high-frequency data to study the volatility prediction of US dollar against Australian dollar. Based on the HAR-RV model, we consider the impact of daily, weekly and monthly volatility on the exchange rate volatility with a lag period, and evaluate their impact on the exchange rate market.

Based on the HAR-RV model, we analyze the impact of daily, weekly and monthly volatility on the exchange rate volatility of the lag 1 period, which are applied to in-sample analysis prediction of the RV of the exchange rate between USD and AUD. The conclusions are proposed accordingly. The HAR-RV model performs well in describing volatility and forecasting accuracy.

The HAR-RV model performs well in terms of prediction accuracy. However, there are still some shortcomings in this paper. First, the original HAR-RV model is simple, but it is less accurate than other HAR-type models. Second, we did not further decompose the fluctuation components to better capture the characteristics of exchange rate fluctuations, which will reduce the prediction accuracy to a certain extent. At present, many researchers consider the impact of leverage effect, spillovers, and geopolitical risks on oil prices volatility. In the future, we would combine the leverage effect and geopolitical risks to the model to predict exchange rate volatility.

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